An Algorithm for Real-Time Facial Landmark Detection Based on Circular Gabor Filters

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Abstract: *This paper presents an algorithm for fast facial feature extraction using circular Gabor filters (CGF). Preliminary parameter selection for the filter calculation is used. An algorithm for parameter selection is also presented. Selection of a limited set of parameters allowed real-timeextraction of facial feature using only one circular Gabor filter.*

***Keywords*:** Biometrics, Face Recognition, Facial Feature Extraction,Circular Gabor Filters.

1. INTRODUCTION

Of great importance in face recognition is fast and robust feature extraction based on the location of specific points in a facial image. Facial feature extraction results in a set of 2D or 3D coordinates which is used in face recognition techniques such as deformable graphs, active appearance or active shape models and face image indexation. A novel algorithm for fast facial feature extraction is presented in this paper.

1D Gabor functions were introduced by D. Gabor in 1946 [1]. J. Daugman extended the functions into 2D representation [2] and applied these for image analysis and compression [3]. Several approaches for face analysis and facial feature extraction employ different sets of Gabor filters. The filters in the sets have different size and orientation. Fasel et. al. used sets of eight or two Gabor filters for facial feature extraction [4]. Weshler et. al. used a set of fourty filters (five sizes and eight orientations) for face image analysis [5]. Convolution with such a number of filters, however, increases computational complexity of face image analysis algorithms and makes them inappropriate to use in real-time applications. Employing rotation invariant circular Gabor filters allowed us to extract appropriate features with a smaller number of filters in the sets thereby reducing the above complexity.

Circular Gabor filters can be applied for extraction of various features. In order to select a feature properly suitable CGFs are to be utilized. An algorithm for optimum parameter set selection is to be used in order to obtain appropriate sets. The algorithm produces a parameter set depending on the feature to be extracted. In order to extract a required feature a suitable set of images is to be used.

2. HYPOTHESIS

A facial feature has a similar pattern on different face images of different persons. The pattern has a similar surface, skin texture and shape. We make the following assumptions:

1. There exists a CGF for a facial feature extraction.
2. A face image is convolved with that filter. After the convolution a local extremum appears in the coordinates of the facial feature.
3. Having found the coordinates of the extremum it is possible to obtain the coordinates of the facial feature and extract it.
4. The task is to find the CGF and the optimum parameter set of the filter.
5. The error of the coordinates mislocation is to be less than 5%.

3. PARAMETER SELECTION

BioID face database [6] was used for testing the results of convolutions with CGFs. The database consists of 1520 face images, each having a set of coordinates for 20 facial features. There is a face image from BioID database in Fig. 1. Coordinates of the facial features are marked by points with numbers. The markup scheme is as follows: 1 : right eye pupil; 2 : left eye pupil; 3 : right mouth corner; 4 : left mouth corner; 5 : outer end of right eye brow; 6 : inner end of right eye brow; 7 : inner end of left eye brow; 8 : outer end of left eye brow; 9 : right temple; 10 : outer corner of right eye; 11 : inner corner of right eye; 12 : inner corner of left eye; 13 : outer corner of left eye; 14 : left temple; 15 : tip of nose; 16 : right nostril; 17 : left nostril; 18 : centre point on outer edge of upper lip; 19 : centre point on outer edge of lower lip; 20 : tip of chin.

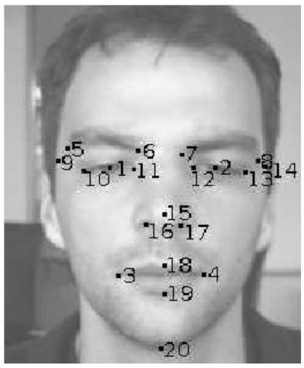

Fig. 1 - Face image with features coordinates marked by points with numbers

A CGF is defined as [7]

$$cg(x, y, \sigma, F) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{2\sigma^2}} e^{2\pi i F\sqrt{x^2+y^2}} \quad (1)$$

where x, y - the spatial coordinates of the CGF, σ - the standard deviation of the Gaussian component of the CGF along x and y, F - the central frequency of the sinusoidal component of the CGF, $i=\sqrt{-1}$. The kernel of the CGF has size sxs. The CGF has a real and an imaginary spatial responses. The real response is given by the cosinusoidal component of the CGF, the imaginary response is given by the sinusoidal component. The kernel of the imaginary response is presented in Fig. 2.

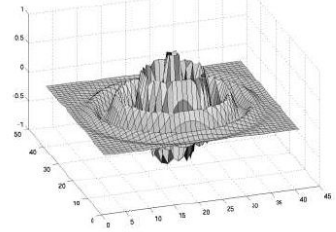

Fig. 2 - Example of the imaginary response of the CGF with *s*=40x40, σ =7, *F*=0,2

Circular Gabor filters with different parameters have to be tested in order to find the optimal parameter set of the CGF for facial feature extraction. In our experiment of the parameter selection we made several numeral assumptions. The face images from BioID database were scaled such that the distances between centers of the pupils were 40 pixels. The sizes of the images were approximately 100x100 pixels. CGFs with different parameters were tested, the kernel sizes of the CGFs in all the experiments were 17x17. The parameters σ and *F* were sequentially selected from domains. The parameter σ has a domain [1..16]. The parameter *F* has a domain [0.01..5]. The parameter σ iteratively changed from 1 to 16 by a step that equals to 2. The parameter *F* iteratively changed from 0.01 to 5 by a step that equals to 0.5. We tested all the parameter combinations changing them in loops. 160 different variants of circular Gabor filters were tested (both real and imaginary responses of the filters). The filters were tested in the feature domains. The domains have size 25x25 pixels. The facial features resided at the centers of the domains.

A new CGF was created by selecting the σ and *F* from the loops. Each domain image of the 20 facial features was convolved with that CGF. Then the convolution results were filtered by a Gaussian. The σ parameter of the Gaussian was 2 and the size was 7x7. After the filtration the results were checked for the presence of extremums. An extremum is defined by a peak on the surface. Fig. 3 (left image) shows the surface of the right eye domain. The surface is represented by image pixel intensities. There is no peak on the surface and there is no distinct extremum in the eye image. The right image in Fig. 3 presents the result of convolution with a CGF and followed by filtration by a Gaussian. The CGF has parameters s=17, $\sigma = 5$, *F*=2.51 and the Gaussian has σ =2 and the dimensions 7x7. There is a distinct peak on the surface on the left image. The coordinates of the peak are the coordinates of the extremum, and the coordinates of the facial feature (right eye pupil).

Algorithm for the parameter selection

Step 1. Select *k* from the loop. If *k*=1520 then **GOTO** Step 7. Select an image I_k from the database.

Step 2. Select the parameters σ_i and F_i from the loops. If the $\sigma_i \geq 16$ and $F_i \geq 5$ then **EXIT**.

Step 3. Compute a CGF_i using (1).

Step 4. Compute the convolutions of the image I_k with the CGF_i in the domains of *M*=20 facial features. The sizes of the domains are 25x25.

Step 5. Perform filtration of the convolution results (computed at Step 4) with the Gaussian. The Gaussian has the $\sigma = 2$ and the size 7x7.

Step 6. Check the *M* facial feature domains for presence of extremums. If an extremum is present in the *j*-th facial feature domain (*j*=1..*M*) then increment the number of extremums c_j: $c_j = c_j + 1$. **GOTO** Step 1.

Step 7. Compute the percentages pc_j, *j*=1..M of the extremums at the facial feature domains using the numbers of extremums c_j.

Step 8. Save the parameters of the CGF_i and the percentages pc_j, *j*=1..*M* of extremums for *M* facial features.

Step 9. GOTO Step 1.

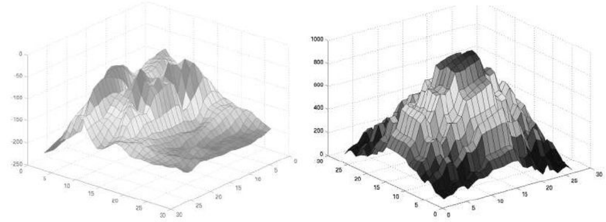

Fig. 3 - Left: the surface of the right eye domain. The surface is represented by pixels intensities. The surface size is 25x25. Right: the surface of the convolution result with the CGF and followed filtration by the Gaussian. The CGF has s=17, σ =5, *F*=2.51 and the Gaussian has σ =2 and size 7x7.

Every CGF either produced or not an extremum at the facial feature coordinates. The numbers of the extremums were saved for every CGF. The percentages of the extremums and the parameters of the CGFs were saved. To obtain the parameters of the CGF the operator has to choose a facial feature type. Selecting the highest percentage of extremums (which appeared at the facial feature coordinates) it is possible to derive the parameters of the CGF. This CGF can be used for feature extraction.

The first column of Table 1 shows the type of the facial feature, the second column shows the maximal percentage of the extremums appeared in the coordinates of the facial feature, the third column shows the type of the CGF response: real or imaginary, the fourth column shows value of the parameter σ of the CGF, the fifth column shows value of the parameter *F* of the CGF. The parameter *s* in the all CGFs was equal to 17.

An experiment was carried out for the right eye pupil extraction. BioID face database was used in the experiment. The images from the face database were scaled. After the scaling the distances between the centers of the pupils were 40 pixels. The sizes of the images were approximately 100x100 pixels. The scaled images were convolved with a CGF. The CGF has the parameter set shown in the first row of Table 1 (*s*=17, σ =5, *F*=2.51, imaginary response). The results of the convolution were filtered by the Gaussian (size 7x7, σ =2). The results of the Gaussian filtration were tested for presence of extremums. Coordinates of the extremums were taken as the coordinates of right eye pupils. The localization error of the coordinates extraction was taken as equal to two pixels (5% of the distance between the eyes). If the localization error between the calculated coordinates and the coordinates from BioID database was less than two pixels (comparing to the distance between the eyes pupil centers) then the coordinates were extracted. The number of images where coordinates of right eye pupil were found with errors was 212 from 1521 images i.e. 14%. Changing the size of the CGF kernel affected neither feature coordinates extraction efficiency nor accuracy. The calculation of the coordinates performed in real-time using Matlab 6.5, Celeron 366 MHz processor, linux 2.6.14. The time of two eye pupil coordinates extraction was approximately 0.035 seconds.

The parameters of the CGFs presented in Table 1 were selected for scaled facial images where the distance between the eyes pupils was 40 pixels. For extraction of the facial features in facial images with different scales the parameters are to be proportional to the distance between the eyes pupils. Table 1contains the parameter sets expressed in percentages relative to the distance between the eyes pupils.

Table 1. CGF parameters for facial features coordinates extraction

Facial feature type (see the markup scheme)	% of correct extremums	real/imaginary	σ	F
1	99	imaginary	5	2.51
2	99,8	imaginary	5	2.51
3	89	real	15	3.01
4	87	real	9	0.51
5	85,5	real	7	0.51
6	93	imaginary	5	2.51
7	94	real	15	3.01
8	88	real	7	0.51
9	82	real	7	0.51
10	92	real	15	3.01
11	87	imaginary	5	2.51
12	89	real	15	3.01
13	91	imaginary	5	2.51
14	88	imaginary	13	1.51
15	93	imaginary	15	1.51
16	96	imaginary	5	2.51
17	95.5	imaginary	5	2.51
18	86	real	7	0.51
19	92	imaginary	5	2.51
20	98	imaginary	5	2.51

During the facial features extraction wrong features with false coordinates can occur. To avoid that the features are to be exctracted in local areas, which are relative to face geometry, and in the order of their robustness to affine changes. The framework for facial feature extraction contains several steps.

At the first step the eyes pupils coordinates are to be exctracted. Using these coordinates the information about the scale of the face and the head orientation can be obtained, and the area of the nostrills is to be localized.

At the second step the coordinates of the nostrils are to be extracted. The face symmetry line parameters can be calculated using the coordinates of the eyes pupils and the coordinates of the nostrils. Ends of the browes, the eye corners and the mouth are to be localized.

At the third step coordinates of the browes, eyes corners and the mouth corners can be extracted accurately. Areas of other facial features are to be localized.

At the fourth step the other features coordinates are to be extracted. Using circular Gabor filters there is no need to rotate the facial image and calculate several Gabor filters with different rotation angle.

4. DISCUSSION

Figure 4 illustrates coordinates extraction of different facial features on BioID face database. The coordinates are extracted with predefined precision.

Coordinates of left and right temple, the tip of nose, the centre point on outer edge of upper lip, the centre point on outer edge of lower lip, the tip of chin should be localized using geometrical model of a face and then extracted in local area.

In order to increase the robustness of this metod coordinates of these facial points can be extracted in a few steps by correction of the local areas position.

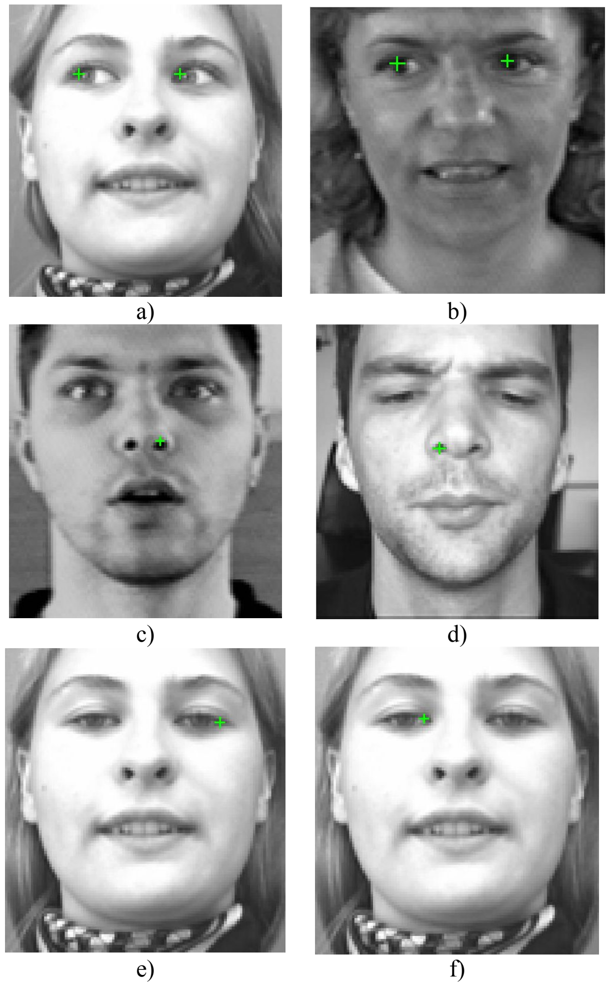

Fig. 4 - Exaples of facial feature coordinates extraction: a,b) center of pupil, c,d) right and left nostrill, e,f) inner and outer eye corner.

Further use of extracted coordinates of facial features usually consists in facial image interpretation and recognition using active appearance models (AAM) [8] or using geometrical model of the face [9].

5. CONCLUSIONS

A novel algorithm for the fast facial features extraction is introduced in the paper. The algorithm uses circular Gabor filters for the coordinates extraction. Parameters for twenty CGFs were selected. The filters allow to calculate extremums at the coordinates of the twenty facial features. Using the CGFs calculated it is possible to extract the coordinates of the twenty facial features. The minimal percentage of the computed extremums was 82% (right temple), the maximal percentage was 99.8% (left eye pupil) on BioID face database consisting of 1520 images. This proves correctness of the selected parameters for the CGFs. The optimal parameter set selection is also a novelty of the algorithm.

An improvement was proposed on facial feature coordinates extraction. Gabor filter-based algorithms generally use different sets of Gabor filters. Circular Gabor filter is symmetrical and rotation invariant. It is possible to reduce the time of facial feature extraction, the number of filters in Gabor filter sets and to extract a rotation invariant feature. The proposed algorithm uses only one circular Gabor filter. The coordinate extraction in our experiments was performed in real-time.

The experiments carried out showed that real responses of circular Gabor filters gave greater percentage of computed extremums in the coordinates of facial features. Change of the size of the CGFs affected neither feature coordinates extraction efficiency nor accuracy.

The algorithm can be applied for extraction of other specific objects of interest, for example, in medical or remotely-sensed images. In order to extract a feature of interest an appropriate image set is to be chosen for the optimal parameter set selection.

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